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Computer simulation of the genetic controller for the EB flue gas treatment process

Zbigniew Moroz,
Jacek Boużyk,
Mieczysław Sowiński,
Andrzej G. Chmielewski

Abstract The use of the computer genetic algorithm (GA) for driving a controller device for the industrial flue gas purification systems employing the electron beam irradiation, has been studied. As the mathematical model of the installation the properly trained artificial neural net (ANN) was used. Various cost functions and optimising strategies of the genetic code were tested. These computer simulations proved, that ANN + GA controller can be sufficiently precise and fast to be applied in real installations.

Key words genetic algorithm controller • flue gas

Z. Moroz
Spectroscopy and Nuclear Technology Division,
The Andrzej Sołtan Institute for Nuclear Studies,
05-400 Otwock/Świerk, Poland,
Białystok Technical University,
45A Wiejska Str., 15-351 Białystok, Poland

J. Boużyk, M. Sowiński✉
Spectroscopy and Nuclear Technology Division,
The Andrzej Sołtan Institute for Nuclear Studies,
05-400 Otwock/Świerk, Poland,
Tel.: +4822/ 7180451, Fax: +4822/ 7793481,
e-mail: sowa@ipj.gov.pl

A. G. Chmielewski
Department of Nuclear Methods in Process Engineering,
Institute of Nuclear Chemistry and Technology,
16 Dorodna Str., 03-195 Warsaw, Poland

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Introduction

Air pollution control is one of the most crucial issues of nowadays. Different technologies have been developed to remove pollutants from industrial off-gases. However, just a few known methods allow to perform multiple-pollutants control in one stage. Among them the most mature is the electron beam technology, which can be used for simultaneous SO_2 and NO_x removal [3, 15–17, 19] and, additionally, as it was demonstrated recently, for volatile organic compounds (VOC) destruction [24].

Industrial plant based on this technology has been in operation since 1998 at Chengdu (China). Other are constructed at Nagoya (Japan) and Pomorzany (Poland). While Japanese plant is constructed on oil fired boilers, two others treat flue gases from coal-fired boilers.

The Polish industrial plant design is based on the tests performed at the pilot plant located at Kawęczyn Power Station [6–8, 10–13, 20]. New solutions that lead to remarkable reduction of power consumption have been applied [4]. The principle of the process is based on humidified and cooled flue gas irradiation with fast electrons (500÷1000 keV), free radicals oxidise SO_2 and NO to SO_3 and NO_2 which, with water and ammonia added, form solid products. The products can be used in agriculture as fertilisers.

On the basis of the experiments algorithm for SO_2 and NO_x removal efficiency as the process parameters function has been presented [9]. The control and monitoring systems have been designed and operated for pilot [26]. Some components of the systems, as e.g. ammonia slip control are based on the same principles as control systems for conventional Flue Gas Desulfurization (FGD) and Selective Catalyctic Reduction (SCR) [25]. In reality, the

Table 1. Influence of different technological parameters on the efficiency of the contamination removal and their relative contribution to the global economical cost function.

No.	Parameter	Efficiency		Cost
		NO_x removal	SO_2 removal	
1	Electron dose	xxxx	xx	xxxx
2	Temperature of flue gas (T)	x	xxxx	xx
3	Humidity (H_2O)	x	xxxx	xx
4	Ammonia (NH_3)	xx	xxx	Ammonia or ammonia water*)
5	NO_{x0} (initial)	xxx	x	
6	SO_{20} (initial)	xx	x	

xxxx – very large; xxx – large; xx – significant; x – small; *) xx-xxxx – dependently on the relation between price of ammonia or ammonia water and sales price of ammonium salts.

process is very complicated because there are some hundreds of different physically-chemical reactions that participate in the process. Their chemical kinetics model was presented in details in [1, 2, 5, 21, 28]. Each of phenomenological models of the process includes a number of internal effective parameters describing the chemical kinetics. These parameters are very difficult to calculate from the first principles, so they must be fixed experimentally. In addition, there are many external technological process parameters, such as initial NO_x and SO_2 concentrations, temperature, humidity, ammonia concentration, flue gas flow, energy and electron beam current. Therefore, contamination of the NO, NO_2 and SO_2 pollutants on the outlet of the installation constitute, in fact, a multiple-parameter event with non-linear dependence on the inlet and technological parameters. Finding all necessary correlation coefficients by a computer expert system is a non-trivial task.

It is just a situation when another technique, namely an application of artificial neural nets (ANN) [27] appears to be superior over computer expert models. In Ref. [23] applicability of the ANN for this purpose was studied in detail. It was proved, that such device could be effectively used as a kind of associative memory, representing the dynamical model of the installation, provided that it was trained by suitable set of the experimental data. It was shown that the properly trained ANN allows predicting final levels of the flue gas contaminants from known initial concentrations of these contaminants and the set of technological parameters.

To apply this neural model to the construction of the process controller device one should go, however, one step further. Now the following problem should be solved: if the initial concentrations of the contaminants were changed, a new set of the technological parameters must be selected in order to keep the final concentrations on the desired level. This is a kind of the reverse problem to the previous one. In Ref. [23] a simple version of the algorithm for the process controller was tested. In this version optimum technological parameters are chosen manually by the operator, having a kind of look-up table calculated in the real time by the program, as help. For a full automatisation of the process this method is not sufficient, however. First of all, in such simple controller each of the parameters is chosen independently on the others, so that correlations between different technological parameters are very difficult to account.

Also, another problem exists, namely a problem of many technologically equivalent solutions: one can reach the same removal of the contamination gases by different choices of some technological parameters. So the problem of choice between such solutions was not solved. Moreover, the so-called "local minima" problem is always present, which is of the pure mathematical origin. This effect is very frequently met in conventional programs for the optimisation of multiparameter functions.

At last, besides of purely technological optimisation, an inclusion of some economical factor is often highly desirable. Already crude analysis of the process reveals, that real costs of keeping different parameters on the desired level vary significantly. As an example, in Table 1 qualitative estimation of the economical importance of the main technological parameters is presented.

All this makes full optimisation problem to be very complicated. Using the genetic algorithm (GA) [22] for the optimisation helps to overcome all these problems. In this paper a combination of the ANN + GA algorithms simulating the process controller is studied. Such solution allows reaching the following goals:

- writing the software for simultaneous optimisation of all technological parameters, taking into account possible strong correlations, which can exist between different parameters,
- easy introduction of an additional economic cost function (CF) to the optimisation,
- obtaining necessary data for the design and performance of a hardware version of the controller.

As a dynamic model of the installation the ANN, that was trained as it was already reported in Ref. [23], is used.

General principle of genetic algorithms (GA's)

Genetic algorithm was invented as a method of the optimisation of the many-parameter non-linear functions and is a result of the observation of evolutionary process in Nature. It is an alternative for the ordinary optimisation task of the multiparameter function. In conventional mathematical methods, not only the knowledge of the optimised function itself, but also its partial derivatives with respect to the optimised parameters, is required. Sometimes, these values are not available or are calculated with large computational effort. Moreover, these methods suffer from the so-called "local minima problem", i.e. automatic stop of the search algorithm on the first local minimum of the function

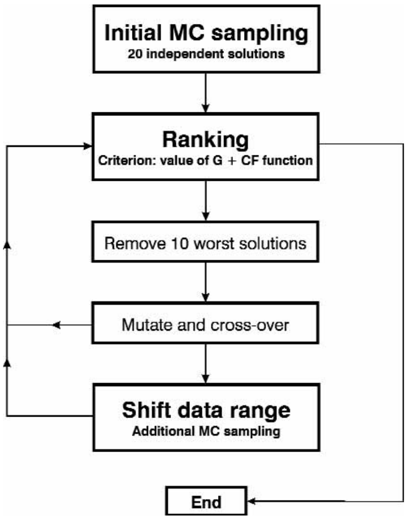

Fig. 1. General principle of the genetic algorithm.

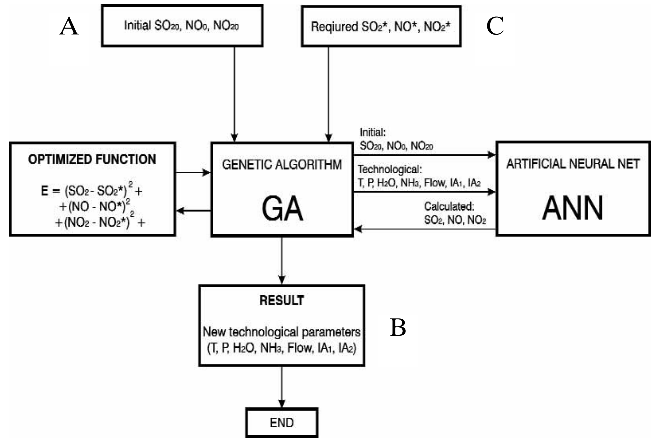

Fig. 2. General scheme of a GA driven controller. A – inlet to the EB installation – initial parameters of flue gas; B – purification process – technological parameters; C – outlet of the EB installation – final parameters of flue gas.

met by the procedure. In such codes finding the global minimum appears to be very complex task, which require sophisticated algorithms and large computational times.

In typical conventional optimisation, say, by means of Monte Carlo method, a set of the independent input vectors **x** is randomly generated and a ranking of the solutions according to the value of the optimised cost function E(**x**) is performed. Only the best solution is kept in the computer memory, while the other, worst cases are erased. Because the whole process is repeated iteratively, better and better solution is gradually selected.

In genetic codes the whole population of individuals (potential vector solutions **x** of the problem) is also generated. But, contrary to the ordinary MC it is not generated at random, but is obtained by multiplication of this part of the previous population, which already positively passed the ranking. This multiplication is done by sequential application of specific transformations, which in analogy with the genetic evolution observed in Nature are called "mutations", "crossovers" etc. In this way, in each repetition of iteration procedure the number of potential solutions is kept constant, but the values of the actual parameters **x** are somewhat better fitted to the final solution, than it was in the earlier iterations. It was shown quite generally, that such procedure leads finally to the solution $\mathbf{x_f}$, for which the value of E($\mathbf{x_f}$) reaches its optimum value (global minimum or maximum), (see Fig. 1).

In the practical realisation of the mutation operator, a single randomly chosen bit of a given parameter x_i is changed. In the crossover operator, number values of x_i and x_j are modified in such a way, that parts of the bit contents of these two numbers are mutually exchanged. Thus, numbers modified by GA contain some bit sequences, which are already better fitted to the final solution. Because of the iterative ranking, the surviving populations become continuously enriched in the "useful" bit sequences.

Genetically driven controllers

Almost every dynamic system, even in the case when it is strongly non-linear, can be effectively coded in artificial neural net (ANN). Thus, the net is able to calculate the actual value of an output function f($\mathbf{p_0}$), where $\mathbf{p_0}$ is a vector of technological parameters driving the installation. Also, it can be taught to predict a new value of the time dependent output function f(t + dt, $\mathbf{p_0}$), provided that the sequence of previous values f(t, $\mathbf{p_0}$), f(t – dt, $\mathbf{p_0}$), f(t – 2dt, $\mathbf{p_0}$) is already known. Thus, the ANN can be easily used to perform fast simulation of the actual behaviour of the process or to alarm the operator about the approaching, its non-desired evolution. For particular case of the cleaning of the flue gas from NO_x and SO_2 by the electron beam irradiation this feature of the ANN's was demonstrated in Ref. [23].

Any controller device is, on the other hand, a tool which is expected to generate new, recommended vector $\mathbf{p_1}$, or the values of the corrections ($\mathbf{p_0}$ – $\mathbf{p_1}$), which assures that the function f($\mathbf{p_1}$) reaches some desired value f_{goal}. Thus, this task is in some sense an inversion of the previous one. Here, one of easily imagined computational techniques is a trial and error procedure (e.g. the conventional Monte Carlo method), in which vectors $\mathbf{p_i}$ are generated at random, and for each $\mathbf{p_i}$ the value of f($\mathbf{p_i}$) is calculated. The $\mathbf{p_1}$ vector giving the best-cost function CF = || f($\mathbf{p_1}$) – f_{goal} || is then selected.

The genetic controller is a device, in which proposed solutions are produced by subsequent genetic mutations and crossovers, applied to some initially selected population. The general scheme of the GA driven controller, with the ANN, representing the dynamical model, is shown in Fig. 2.

Further, we concentrate ourselves exclusively on the installation for the cleaning of the flue gas by EB irradiation. The parameters in Fig. 2 and the corresponding cost function are selected already having in mind this particular task.

The EB irradiation installation. Computerised control system and a multidimensional event structure

In the studied example of the installation we have assumed three separate flue gas lines (see Fig. 3). The first and second lines consist of process vessel, where gas is irradiated by electron beams from two separate accelerators.

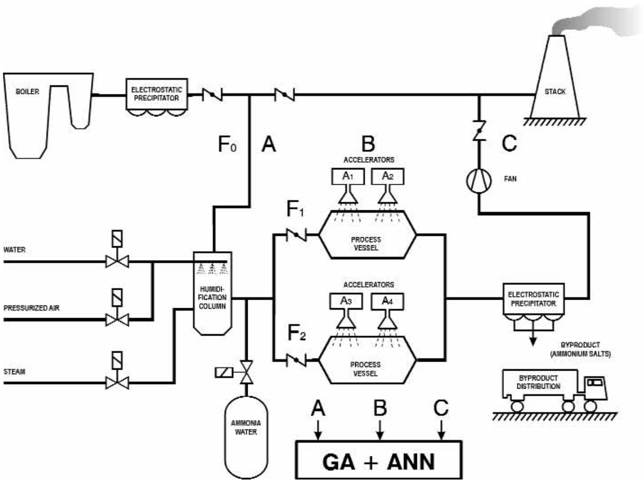

Fig. 3. Structure of the installation.

The third line is a parallel bypass, through which a part of the raw gas flows. These three flows of the gas are then mixed and discharged through the stack to the atmosphere. For a discussion of some specific features of such installation, see Refs. [6, 8, 10].

The installation is equipped in a computer monitoring and control system, which in the future should allow full automatisation of the process. Quite generally, such computerised system consists of three main parts:

(i) the monitoring, or diagnostic part, that consists of a number of detectors and other measuring devices, monitoring the actual status of the installation,
(ii) analysing part, which uses the monitoring data by means of some model or simulating programs and proposes new settings of the technological parameters, expected to optimise the desired output values,
(iii) effectors, which work out the suitable signals for interfaces of various devices, like valves, pumps, motors etc.

During its operation, the computerised monitoring system reads data characterising the actual status of the installation and it updates the settings of the technological parameters to achieve the desired outputs.

The installation consists of two symmetric lines. Therefore, the number of independent parameters to be controlled can be substantially suppressed and the basic mathematical model of the GA controller of only one irradiation line is necessary. But in a practical hardware implementation one must properly combine two such controllers. The corresponding extension that is required for this case is rather straightforward.

The presently discussed EB irradiation line the set of data that is continuously monitored by the system consists of:

(i) initial concentrations of the exhaust gas: NO_0, NO_{20}, SO_{20},
(ii) technological parameters of the lines 1 or 2:
   – average gas temperature (T) in the inlet of the reaction vessel,
   – gas pressure (P),
   – gas humidity (H_2O),
   – ammonia concentration (NH_3) (or stoichiometric ratio),
   – gas flow (FL),
   – parameters of electron accelerators: (electron energy – EA_1, EA_2, beam current – IA_1, IA_2, or calculated equivalent dose – D).

We assume the accelerator energy to be fixed ($EA_1 = EA_2 = 800$ keV). For each line we have also three values of final concentrations measured, i.e. NO, NO_2 and SO_2.

Thus, for each individual line we have dealing with the (3 + 7)-dimensional parameter set

(1) $\{x_I\} = \{NO_0, NO_{20}, SO_{20}; T, P, H_2O, NH_3, FL, IA_1, IA_2\}$

and the required set of output concentrations

(2) $\{R_i\} = \{NO^*, NO_2{}^*, SO_2{}^*\}$.

Such events are continuously extracted from the readings of the monitoring system of the installation.

If two irradiation lines are run in parallel, the following quantities are identical in both lines: Electron energies $EA_1 = EA_2$, T, P, H_2O, and NH_3. So, that only gas flows (FL_1 and FL_2) and all two beam currents are set independently.

The algorithm of basic genetic controller

In this work we use the model represented by the trained ANN obtained in the Ref. [23]. The following parameters of the multilayered perceptron have been accepted: the net architecture was of the {10:8:8:3} type. Ten input neurons were fed by the initial $SO_2{}^0$ and $NO_x{}^0$ values, two accelerator beam currents and remaining technological parameters {T, P, H_2O, NH_3, flow}. Three output neurons represented the reduction coefficients of the SO_2 and NO_x concentrations. To optimize weights and biases of the neurons the back-propagation learning rule was used. Both, teaching and testing files contained 3000 multidimensional events each. The learning parameter α was varied between 0.001 and 0.8 and the momentum term was 0.01.

This learning procedure appeared to be very effective, so that no special attempts were necessary to optimize the net architecture and associated parameters. In our opinion it is due to the fact, that the mathematical simulator of the events [1, 2] which was intentionally invented as a possibly simple system of coupled differential equations, contain solutions which are free of very complex nonlinearities. However in the future, during teaching by real experimental data supplied directly by the EB installation, such optimization may appear to be unavoidable.

The GA used in this work was written by one of the authors, as a simple version of the classical genetic procedure. The program works in binary representation. Each optimized quantity corresponds to the chromosome and each bit is treated as a separate gene. Only two genetic operators, namely the crossover and mutation, are used. The crossover operation is performed in three steps: (i) random selection of two chromosomes, (ii) random choice of the separation line (a bit number) of the chromosomes and (iii) the execution of the proper crossing operation. The mutation operation consist of two steps: (i) random selection of the candidate and (ii) random choice of the bit subjected to the 0 <= => 1 transformation.

The present version of the program allowed the population not larger than 100 events, the crossover probability $p_c \le 1$ and the mutation probability $p_m \le 0.3$. In the ranking procedure the percentage of the accepted events can be varied between $0.5 \le p_{acc} \le 0.1$ of the total population. However, these values could be easily changed. In our calculations, as a standard we used population only 20 events, $p_c = 0.8$, $p_m = 0.1$ and $p_{acc} = 0.5$.

We found that with our ANN model and the goal functions used by us, a reasonable fit was rather easily obtained already after some few thousands of the iterations. This would suggest that the genetic optimization procedure is almost trivially easy, so that one can even wonder whether it is really necessary to use the GA instead of some conventional algorithm. However, we think that the actual installation can exhibit, however, much more complex behaviour, which can made the use of the GA to be unavoidable. Also, the use of much larger population and some optimization of other parameters of the genetic procedure, can be also necessary.

Accordingly, the following general scheme of the GA controller can be worked-out:

(i) The GA program chooses some number, say 20, of the independent sets of the technological parameters {T, P, H_2O, NH_3, FL, IA_1, IA_2}. These parameters are sent to the input of the ANN, together with the actual initial parameters {NO_0, NO_{20}, SO_{20}} produce 20 different results of {NO, NO_2 SO_2}. These sets are generated by the conventional MC method in the hyper-cube of technological parameters.
(ii) Values of {NO, NO_2, SO_2} are used to calculate the goal function E, as follows:

(3) $E = G_0 + CF$,

(4) $G_0 = (NO - NO^*)^2 + (NO_2 - NO_2{}^*)^2 + (SO_2 - SO_2{}^*)^2$

where NO^*, $NO_2{}^*$, $SO_2{}^*$ are the required values, CF is the additional cost function, which will be described later.
(iii) These 20 solutions are subjected to the ranking procedure, in which they are ordered according to the values of their E-functions.
(iv) The worst 10 solutions are erased and 10 free places are then filled by 10 new solutions obtained from the parameters of the first 10 sets by applying the mutation and crossover operators to the technological parameters.
(v) This new set of the solutions is subjected to the next ranking procedure and the whole process is iteratively repeated until the E-function reach the desired low value, when the whole process is stopped.
(vi) From time to time the limits are shifted and to the statistics of the solutions some admixture of fresh MC solutions is added. This is done so because that it may happen that the initial MC sampling hyper-cube does not contain any minimum.

The whole procedure has some disadvantage in the case when the function E, for different parameter sets, has some number equally good solutions. This is just the case of our installation, where the desired levels of the final contamination (i.e. $E = G_0$ for $CF = 0$) can be often reached by different parameter settings. Therefore an extra criterion differentiating the solutions, being otherwise fully equivalent, must be applied.

In principle, this criterion can be chosen quite freely. For example, it can be a function limiting the allowed speed of the changes of some technological parameters or, as it is in our work, it is the economical cost function. Each additional cost function should be multiplied by some scaling factor which controls the relative contribution of the CF to the total goal function as well as normalizes the units in which the G_0 and CF functions are expressed.

Used by us economical cost function is a linear combination of differences between the actual values of the controlled parameters and their standard settings:

(5) $CF = \lambda[a_T(T - T_{standard}) + a_{H_2O}(H_2O - H_2O_{standard}) + ...]$

The coefficients a_i set the relative weights for different factors and should be calculated from economical data. The common scaling factor λ must be chosen so that the total contribution of CF to the E function is small. In this work, in the absence of the real economical data, all these coefficients were chosen quite arbitrarily, because at present only ability of the CF function to differentiate the otherwise equivalent solutions is really important.

Performance and test of the controller

To test the controller simulator some average levels of the initial concentrations and technological parameters were chosen. Then, additional random fluctuations were simulated using conventional random number generator and added to the average levels. In this way hundred events of simulated values $\{x_I\}$ = {NO_0, NO_{20}, SO_{20}; T, H_2O, NH_3, FL, IA_1, IA_2} were generated. Each event was treated as the input for the GA simulator which, after run of the GA optimising algorithm, proposed new values of the technological parameters which assure the final gas concentrations equal to the desired $NO_x{}^*$ and $SO_2{}^*$, together with minimisation of rather arbitrarily chosen "economical" CF function. In Fig. 4a values of NO_{x0}, and SO_{20} are presented for all 100 pseudo-random samples. The required values of the final concentrations were chosen quite arbitrarily as $NO_x{}^* = 100$ ppm and $SO_2 = 70$ ppm.

It is worthwhile to stress, that the values of NO_{x0}, and SO_{20} adapted in this test were generated quite randomly. The amplitudes of these random components were intentionally chosen to exceed significantly values of the changes of the initial concentrations measured in the past in the EP Pomorzany, prior to the completion of the cleaning instal-

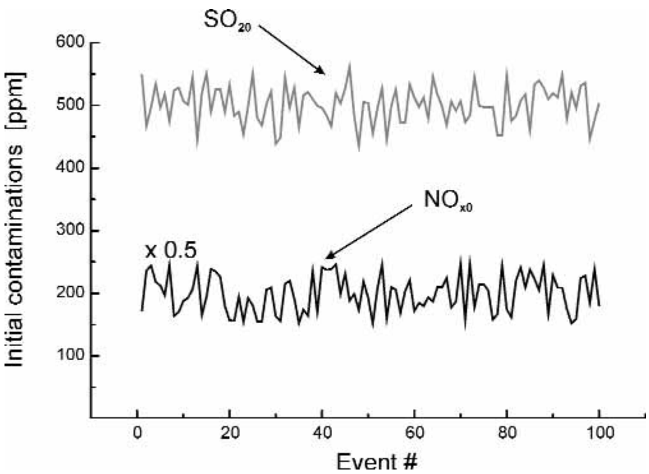

Fig. 4a. Initial flue gas contamination from randomly chosen 100 events.

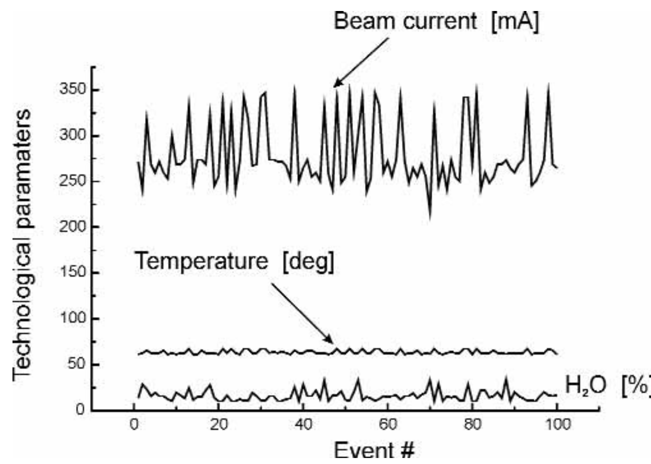

Fig. 4b. Technological parameters: T, H_2O, and beam current for the same events.

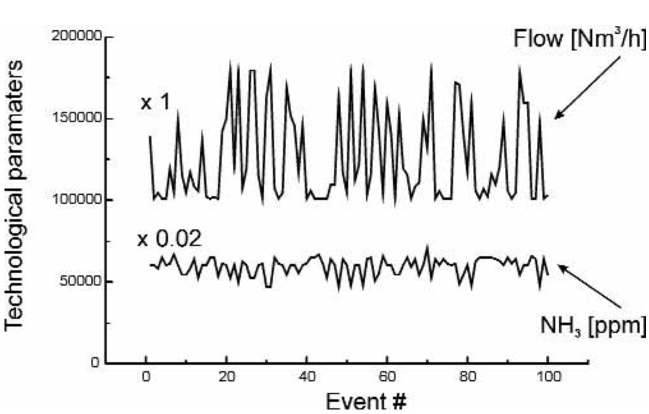

Fig. 4c. Technological parameters: NH_3 and gas flow for the same events.

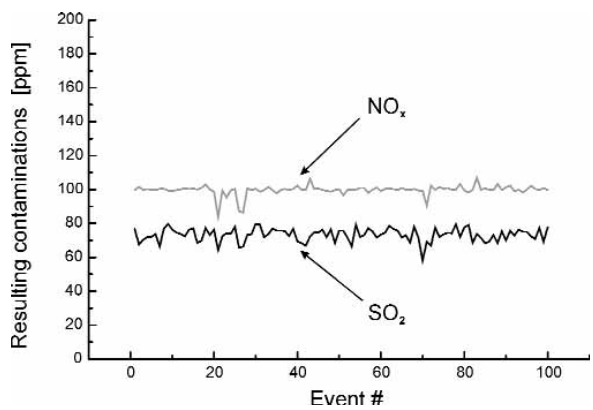

Fig. 4d. Final flue gas contamination found by GA controller. Chosen required values were 100 and 70 ppm for NO_x and SO_2 correspondingly. The corresponding technological parameters chosen by the controller, those shown in Figs. 4a, b and c.

lation [18]. This was done to check reliability of proposed ANN + GA controller in the conditions, which may accidentally deviate from those which are expected at present. In Figs. 4b, 4c the corresponding values of the technological parameters, proposed by GA controller to balance the random changes of the initial concentrations, are shown.

In Fig. 4d resulting final concentrations of $NO_x = NO + NO_2$ and SO_2, as calculated by the ANN for the technological parameters proposed by GA controller are presented. The deviations of these values from the required NO_x* and SO_2* ones represent, in fact, the instrumental error of the GA controller. It depends on the quality of the ANN training and on the number of the iterations assumed in the GA controller. Both these factors are not finally set, as yet, because the simulated data used in the present work are certainly approximate. It is believed that during the final training of the ANN, using true experimental data from the working installation, this error will be diminished significantly.

To test whether GA controller responds correctly to different sets of the goal values, the last ones were changed few times during the calculations. In all cases a good agreement between required and final values was obtained. Thus, this point was verified positively. Examples of numerical values proposed by the ANN + GA algorithm are shown in Table 2.

In curves presented in Figs. 4b, 4c one can observe, that some of the parameters chosen by the controller are almost constant. Here it is clearly seen for the gas temperature (T). It must be realized that the particular cost function always favours some settings of the technological parameters. In the present choice of the CF just temperature is kept almost constant. After changing the economical preferences, the same controller could be more resistive against the changes of another parameter, allowing the temperature to jump much more freely. Of course, it may suggest that such almost constant parameter can be simply excluded from the optimization. Whether it is so or not, can be decided only after final choice of the economical CF and after some play with the real experimental data.

General performance of the GA controller depends on the choice of the goal function E. In the course of this work this function was changed and different behaviour of the controller was observed.

Purely technological cost function

First tests were performed with function $E = G_0$, as defined in point 4 with economical cost function CF = 0. In this case, as it was mentioned above, G_0 function may possess many equivalent minima for different settings of the technological parameters. Therefore, in some cases, the GA

Event	Initial		Final			Proposed technological parameters					
no.	NO_{x0}	SO_{20}	NO	NO_2	SO_2	H_2O	NH_3	T	FL	IA_1	Dose
1	341.3	567.5	78.0	22.3	79.6	12.2	1207.2	62.8	101970.8	230.5	10.9
2	473.0	481.6	73.1	26.9	79.3	16.7	1089.9	71.6	105795.9	328.1	15.5
3	488.1	495.8	73.2	27.4	79.7	19.1	1089.9	71.6	106004.0	344.0	16.3
4	436.9	500.0	74.8	25.2	80.4	16.7	1089.9	70.2	112006.8	323.4	15.3
5	423.8	496.6	75.3	24.4	80.4	10.3	1089.9	71.6	107595.8	310.2	14.7
6	393.5	471.0	76.0	24.0	80.5	10.5	1089.3	70.2	112595.8	289.1	13.7
7	357.8	472.6	74.9	25.8	79.4	16.7	1108.7	68.8	167670.9	271.8	12.9
8	477.0	490.0	73.5	26.6	79.4	16.7	1089.9	71.7	102670.9	337.5	16.0
9	456.1	501.7	73.7	25.9	80.4	16.6	1089.9	71.6	119545.9	346.8	16.4
10	487.5	493.1	73.5	27.1	79.8	18.7	1089.9	71.7	102045.9	342.2	16.2

Table 2. Some numerical values proposed by ANN + GA program.

Fixed values: $NO_{20} = 0$; $P = 0.9$; $IA_1 = IA_2$. Goal: $NO_x = 100$; $SO_2 = 70$.

algorithm has difficulties in taking decision, which of those minima take as the target value. This can be observed as dramatic slowing-down of the iterative process, with the value of G_0 function still being relatively large.

Technological and economical cost function

In the next group of tests function $E = G_0 + CF$ was chosen, so that the degeneracy of different minima was removed. Then, the global minimum for which GA is searching is mathematically somewhat different than that for $E = G_0$. This is so, because the CF has their own minimum and the global minimum for full E function is a kind of compromise. In fact, looking for the solutions that are proposed by GA it could be observed that such final solution is chosen, for which separate contributions to E from G_0 and CF are almost equal.

Here two problems arise: (i) proposed solution is somewhat shifted by CF from that giving $G_0 = 0$, i.e. from their ideal desired values, and (ii) a slowing-down is observed at the end of the iterative process, indicating that with good approximation right solutions are reached. At the last part of the process, when both components G_0 and CF are already small, the speed of the convergence is small. These two features strongly depend on the choice of the CF function. Anyway, there are many cost functions, for which the iteration duration time is still not prohibitive. Thus, it appears that the GA method is fully suitable for the dynamical processes that are relatively slow. In fact, considered by us EB cleaning process is slow enough.

Variable cost function

Third group of tests was performed using the E function varying during progress of the iteration procedure. For simplicity, we used the following form:

(6) $E = G_0 + CF$ for the first 500 iterations,

(7) $E = G_0$ for further iterations,

It means that at the beginning of the iteration process, the CF function was switched-on, directing to the solution close to that forced by the condition $G_0 + CF = \text{min.}$ and then, after 500 iterations, CF function was switched-off, allowing the iterations to go freely toward the closest $G_0 = \text{min.}$ solution. As a result, a very good performance of the GA controller was obtained. A good accuracy of the solutions in comparison with the desired concentration levels was reached in a relatively small number of the iterations. In our conditions, using standard PC computer with 75 MHz Pentium processor, the iteration process is usually stabilised after no more than 1000 iterations, i.e. after ca. 30 sec of the operation.

Taking into attention that the whole industrial process is rather slow (valuable changes last minutes, rather than seconds), such reaction time of the controller program is totally satisfactory. Certainly, it can be further speeded, by using faster processor like, say, 330 MHz, being a standard now, and further optimising the CF function.

Hardware implementation of the ANN + GA controller

The present work is dedicated to the mathematical analysis of the performance of the ANN + GA controller software. For the hardware implementation of such controller the following three steps must be performed:

1. Independent algorithms for two irradiation lines must be properly synthesised. In such synthesis the main features are that the economical cost function must simultaneously include independently controlled parameters from both lines (Fig. 3). Also, required final values of the flue gas contamination components must concern the averages over both lines, rather than of the individual lines separately. This, as it was written before, it is not a very difficult task.
2. The set of parameters used in the present analysis describe the physical conditions in the irradiation volumes and must be further translated to the settings of the particular devices of the installation automatics. This last translator is shown in Fig. 5 as a block labelled by "W_1" and by subsequent symbols of the device drivers.
3. The host PC computer (only in an industrial performance), must be equipped with transmission lines, which allow to read the data directly from the monitoring system of the installation and, after the ANN + GA program ends its action, to pass the output signals to the device drivers.

Discussion and conclusions

In this work, applicability of the controller driven by genetic algorithm was studied, as a tool for the control the process of cleaning of the flue gas by EB irradiation. In the computer emulator the dynamic model of the installation

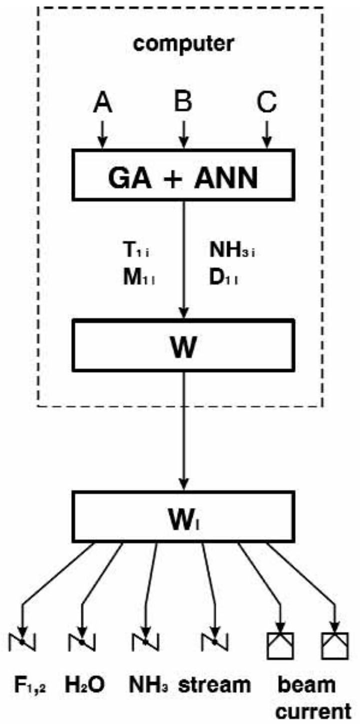

Fig. 5. Block scheme of the process controller.

was represented by properly trained ANN. Details of the ANN were published in Ref. [1]. Genetic algorithm was used to optimise goal function E, which was assumed to have two components:
First "technological" component is

(8) $G_0 = (NO - NO^*)^2 + (NO_2 - NO_2^*)^2 + (SO_2 - SO_2^*)^2$

whose minimum is for $NO = NO^*$, $NO_2 = NO_2^*$ and $SO_2 = SO_2^*$ and the second component is the "economical" cost function CF, being the function of the technological parameters and reflecting the economical costs of the run.

This CF function allowed to differentiate local minima of G_0, which otherwise are degenerated. A number of tests done with different cost functions have shown that the best performance of the controller one gets if at the beginning a nonzero CF function directs the iteration process toward the solution closest to that induced by CF = 0 condition. Then, after a number of iterations the CF function is forced to be zero, thus allowing the iteration to fall freely toward the closest solution induced by the condition $G_0 = 0$. In this way, both the desired accuracy of the final solution and the iteration time short enough are simultaneously reached.

We conclude, that a GA driven controller should be a device very well suited to the problem, provided that the experimental data from the working installation are already reach enough to allow training the artificial neural network. In the beginning stage, when these experimental data are not yet available in a desired quantity, one can use one of existing theoretical expert models of such installation. We presented one of such models in Ref. [23].

The present paper does not propose any final version algorithm of the ANN + GA controller, directly suitable for the control of the EB installation. Quite the contrary, it contains only the message for future designers of such device, that the ANN + GA algorithm can relatively simple handle the main problems.

To obtain final version of the controller, one must start from the teaching of the ANN with the real data, not the simulated ones, as it was already stressed in the conclusions in the paper [23]. During this stage the final optimization of the ANN should be done, including some experiments with the net architecture and parameters. Also, the run of the installation will supply us in the information, whether the standard ANN with constant weights is satisfactory or, because of the drift of the installation parameters, a kind of periodical or permanent actualization of the weights is necessary. From the programming point of view, the implantation of such adaptive learning with moving sampling horizon, is not a difficult task.

Having the ANN already trained, also some optimizations of the GA algorithm will be probably necessary. At first, the question should be reconsidered about the choice of some standard genetic algorithm, which can eventually replace the simple one, used in the present work. In principle, such play with the real data can even show that the optimizing algorithm can be much simpler, of the conventional type. On the other hand, if some other input quantities being a subject of the control will be used, requirements to the optimization algorithm may appear to be much more restrictive and the use of more sophisticated GA will appear unavoidable. After a version the GA algorithm will prove his advantage, the controller should be constructed following the further rules given in the previous chapter. Then, also some internal parameters of the GA algorithm can be optimized. It may concern the population of the events subjected to the sampling, mutation and crossover coefficients etc. Finally, the use of the right cost function should be studied and the scaling coefficient λ experimentally chosen.

The ANN + GA method presented here can be applied not only to the presently discussed installation but also to optimise any other flue cleaning installation, employing more standard methods. For example, those methods, which are using the semidry or dry method [14]. The only condition is that a reliable set of data, measured on the running installation or simulated using a good simulator, should be in the disposal. It concerns the initial and final gas contamination as well as the technological parameters, such as the energy and the sorbent consumption, the sorbent contamination of the waste material etc.

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